Habitat International 73 (2018) 16–24

Contents lists available at ScienceDirect

Habitat International

journal homepage: www.elsevier.com/locate/habitatint

Consumption based approach of carbon footprint analysis in urban slum and non-slum areas of Rawalpindi

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ARTICLE INFO

Keywords:
Household carbon footprint
Household consumption
Rapid urbanization
Environmental load
Slum areas
Non-slum areas

ABSTRACT

UN Habitat estimates that more than fifty percent of global population is now urbanized. Carbon emission, urbanization and climate change are intricately linked with each other. To sustain growing household energy demand in Pakistan, carbon emission has substantially increased, which is reflected by country's rank among climate vulnerable nations. Unsustainable use of energy is a major contributor of urban carbon footprint. Study of household carbon footprint is thus felt imperative to identify key factors of carbon footprint increase. This study aims to compare the carbon footprint of urban slum (Kachi Abadi, Khayaban-e-Sirsyed) and non-slum areas (Bahria Town, Gulraiz Colony) of Rawalpindi city to assess the environmental burden in the form of CO_2 emissions generated at the household consumption practices. Results clearly indicate that the household carbon footprint of non-slum areas is higher than urban slum areas. Carbon footprint of non-slum areas shows highly significant increment along with the increasing monthly income of their inhabitants ($r = 0.49$ $p = .02$; $r = 0.79$ $p < .01$). Regression analysis revealed significant impact of individual use of personal vehicles on increasing carbon footprint in non-slum areas ($R^2 = 0.61$; $p < .01$). Findings presented here substantially contribute in highlighting key household parameters that actually depicts consumption patterns linked with carbon emission. We conclude that the escalating household consumption by attaining luxurious life style leads to increase in carbon footprint significantly at domestic level, which could be reduced by using less carbon intensive products.

1. Introduction

Pakistan is considered as 12th most vulnerable country as far as climatic changes are concerned, in spite of the fact that Pakistan itself contributes very little to the overall emissions of the Greenhouse Gases (GHGs) (Lenzen & Murray, 2001). Currently Pakistan contributes 0.8% of the aggregate worldwide GHG emission and ranking 135th globally on the basis of per capita emissions (Athar, Aijaz, & Mumtaz, 2009). In Pakistan, different anthropogenic activities like extensive use of fossil fuels in energy production results in increasing GHGs concentration and CO_2 emissions have the highest share (60%) among all the greenhouse gases (Khan & Jamil, 2015). As the carbon emissions are directly associated with the consumption of fossil fuels which is necessary to meet the energy requirements of growing population in the country. According to the '6th Population and Housing Census 2017', current population is 207.8 million and Pakistan is now sixth most populous nation of the world. The trend of CO_2 emissions in Pakistan is rising alarmingly with the rapid increase of urban share in total population (Fig. 1). Per capita energy use in Pakistan has increased from 272 Kg to 499 Kg in 1971–2008 which is responsible for increasing GHGs emissions. In Asian countries, transport sector is another main source of CO_2 emissions although over the last 25 years it shares remains constant at about 10% globally. However, carbon emissions are directly associated with the rising income which results in higher levels of car ownership and their usage resulting significant increase in CO_2 emissions (Timilsina & Shrestha, 2009).

The measurement of the CO_2 and other carbon compounds released due to the utilization of petroleum products by a specific individual, gathering and so forth is known as carbon footprint. These carbon emissions may be either direct or indirect. Primary footprints are the estimations of direct carbon dioxide emissions released because of domestic energy utilization and transportation such as cars and planes and consuming of non-renewable energy resources. Whereas the estimation of indirect CO_2 released from the whole life cycle of products and services from cradle to grave is said to be secondary footprints (Tukker & Jansen, 2006). The household carbon footprint includes both the direct emissions from the energy, gas or petrol consumption such as automobiles used in home contributes in direct carbon emissions whereas indirect emissions comes from the household products such as televisions, furniture etc till their disposal (Kerkhof et al., 2009).

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https://doi.org/10.1016/j.habitatint.2017.12.012
Received 29 August 2017; Received in revised form 21 December 2017; Accepted 27 December 2017
Available online 04 January 2018

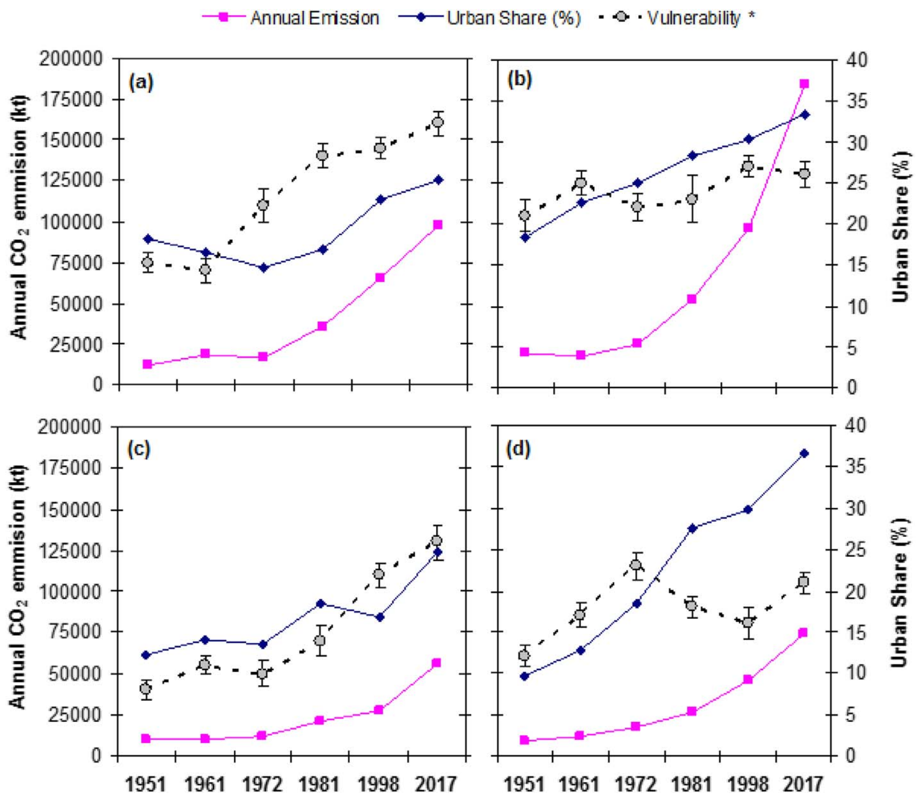

Fig. 1. Annual CO_2 emissions from Pakistan with urban share of total population recorded at the time of census in the given years for major cities (a) Rawalpindi, (b) Lahore, (c) Quetta and (d) Attock. * Vulnerability to carbon emission led climate change is tapped on a scale 0 to 50 for these cities with rising scale showing more vulnerable.

Different studies have analyzed carbon footprint at household and industrial level in different areas of the world (Shirley, Jones, & Kammen, 2012). Carbon footprints of typical household were assessed in United States Virgin Island (USVI) and energy is considered as the critical monetary driver for financial development and social advancement. In Canada 44% of total country's GHGs are generated from the household (Statistics Canada, 2011). Incredible affiliation is seen between household CO_2 emissions and the provision of certain functional needs for example shelter and food (Druckman & Jackson, 2008) (see Table 1).

Carbon footprint calculators available online have shown promising evaluation results all over the world. Several studies have repeatedly demonstrated that input data either in superficial to detailed form can be analyzed using online calculators to depict human impact on environment (Pandey, Agrawal, & Pandey, 2011) such as household carbon footprint in US (Jones and Kammen, 2011), household energy and carbon calculation in UK (Padgett, Steinemann, Clarke, & Vandenbergh, 2008) and university carbon footprint in Thailand on the basis of online calculator (Utaraskul, 2015). Carbon calculators accounted for food consumption are acknowledged in US to reduce the impacts arising indirectly from our diet (Kim & Neff, 2009). Approach developed to analyze personal carbon footprint based on the ubiquitous activity through online calculator allows users to identify their footprints and act accordingly (Rahman, O'Brien, Ahamed, Zhang, & Liu, 2011).

Evaluation of housing sector carbon footprint is recently recognized highly useful because it not only provides baseline information (Bendewald & Zhai, 2013) but also plays a significant role in identifying prime contributors of CO_2 emission in urban areas (Gardezi et al., 2016). Unfortunately scarce data about carbon footprint in Pakistan has led to multiple uncertainties to formulate effective climate adaptation policies hence it is important to instigate such study in urbanized areas of Pakistan which represents the entire profile of households and its key factors contributing in household carbon footprint. After Karachi, Lahore and Faisalabad, Rawalpindi is the fourth largest city of Pakistan so it is selected as the case study area (Fig. 2). Rawalpindi and Islamabad are considered the twin cities of Punjab. Its population was 180,000 at the time of independence but due to urban planning, better services and master plans its population was increased up to 4.5 million in 2017. Although Rawalpindi has some developed areas like Bahria Town and Gulraiz Colony where people live lavishly but it also has most neglected slum areas like Kachi Abadi and Khayaban-e-Sirsyed. People living in slum areas are mostly deprived of houses, hence exposed them to external climatic conditions, and they don't have an easy access to safe water and food, electricity and proper sanitation system where as non-slum areas are the urbanized and developed areas in Rawalpindi (Rashid et al., 2018). A case study approach was developed here to evaluate the household carbon footprint. We aimed to compare carbon dioxide emissions of slum and non slum areas of Rawalpindi city and to identify parameter(s) that have higher contribution in carbon footprints.

2. Materials and methods

This study was conducted in urban localities of Rawalpindi city where population of two slum areas i.e. Khayaban-e-Sirsyed and Kachi Abadi and two non slum areas such as Bahria Town and Gulraiz Colony were selected for data collection. Completely randomized and block sampling technique was used to collect data from the selected two main blocks i.e. slum and non-slum areas. Basic criteria for their selection is that as Bahria Town and Gulraiz Colony are the developed and most urbanized areas of Rawalpindi as compared to any other area in this city and slum areas like Khayaban-e-Sirsyed and Kachi Abadi are most neglected areas of Rawalpindi so it make an interesting comparison in their household consumption and CO_2 emissions.

Self-structured questionnaire was used to gather primary data regarding demographic variables from each area randomly. Samples of 80 questionnaires were filled by selected population. Questionnaires were filled on the basis of household consumption. Different parameters were included to estimate consumption pattern such as electricity consumption, as Bahria Town has its own electricity and grid station and they provide electricity to their residents. Data of electricity (kWh) was collected through household monthly bills. In transport, distance traveled in (Km), of all family members from their home to working places

Table 1
Literature review pertaining to CO_2 emission estimates using various household parameters.

Country and tracking year	Household parameters	CO_2 tracking method	Emission estimate	Reference
China (2017)	Electricity for space heating, fuel use during cooking, and transportation	Based on IPCC CO_2 Emissions = fuel consumption × [fuel carbon content • fuel calorific value • fuel oxidation rate] × emission factor	Cooking & heating = 43% Transportation = 30% Space heating = 27%	Yang & Liu, 2017
UK (2016)	Gas, electricity and personal transport	CO_2 Emissions = Consumption × Emission factor	Gas = 46% Electricity = 32% Personal transport = 22%	Allinson et al., 2016
USA (2008)	Education, Health, Communication, Clothing, Miscellaneous, Recreation/culture, Utilities, Furnishing, Housing, Personal transport, Tobacco, Restaurants and hotels, Food and beverages at home	CO_2 Emissions = Consumption × Emission factor	Education = 2.5% Health = 7.5% Communication = 1.6% Clothing = 3.3% Miscellaneous = 10% Recreation/culture = 2.5% Utilities = 25.8% Furnishing = 3.3% Housing = 4.1% Personal transport = 26.6% Tobacco = 1.6% Restaurants and hotels = 4.1% Food and beverages at home = 6.6%	Weber & Matthews, 2008
US (2012)	Transport, home energy, food, goods and services	Cool climate network (online carbon calculator) CO_2 Emissions = Consumption × Emission factor	Transportation = 24% Home energy = 31% Services = 8% Goods = 10% Food = 18% Waste and water = 9%	Shirley et al., 2012
US (2008)	Electricity, Natural Gas, Fuel oil, Propane, Transportation, Personal air travel	Online carbon calculator	Electricity = 26% Natural gas = 17.3% Fuel oil = 22.5% Propane = 16.6% Personal vehicle use = 16.5% Personal air travel = 0.8%	Padgett et al., 2008
US (2009)	Transportation, energy use, waste/recycling, food consumption, water use and other products purchase	Online carbon calculator	Transport = 94% Energy use = 84% Waste/recycling = 35% Food consumption = 25% Water use = 18% Other product purchase = 14%	Kim & Neff, 2009
China (2007)	Raw coal, Other washed coal, Other gas, LPG, Heat, Electricity, Food, Clothing, Facilities, Health, Transport, Education, Housing	CF = ΣM × EF	Raw coal = 4.61% Other washed coal = 1.2% Other gas = 1.09% LPG = 0.9% Heat = 15.6% Electricity = 10.5% Food = 17.1% Clothing = 6.9% Facilities = 4.4% Health = 7.7% Transport = 1.3% Education = 16.4% Housing = 4.3% Others = 7.4%	Tian, Geng, Dong et al., 2016; Tian, Geng Dai et al., 2016
Estonia (2011)	Food and beverages Clothing and footwear Housing, water, electricity, gas and other fuels Furnishings, household equipment and routine maintenance of the house Health Transport Communications Recreation and culture Education Restaurants and hotels	Input output model	Food and beverages = 17.2% Clothing and footwear = 1.81% Housing, water, electricity, gas and other fuels = 41.8% Furnishing, housing equipment and routine maintenance of the house = 7.2% Health = 1.81% Transport = 18.1% Communication = 0.9% Recreation and culture = 4.5% Education = 0.9% Restaurants and hotels = 3.6% Miscellaneous goods and services = 1.8%	Brizga, Feng, & Hubacek, 2017
Latvia (2011)	Food and beverages Clothing and footwear Housing, water, electricity, gas and other fuels Furnishings, household equipment and routine maintenance of the house Health Transport Communications Recreation and culture Education Restaurants and hotels	Input output model	Food and beverages = 29.8% Clothing and footwear = 1.49% Housing, water, electricity, gas and other fuels = 26.8% Furnishing, housing equipment and routine maintenance of the house = 7.4% Health = 1.4% Transport = 20.8% Communication = 0% Recreation and culture = 5.97% Education = 0% Restaurants and hotels = 2.9% Miscellaneous goods and services = 2.9%	Brizga et al., 2017
Lithuania (2011)	Food and beverages Clothing and footwear Housing, water, electricity, gas and other fuels Furnishings, household equipment and routine maintenance of the house Health	Input output model	Food and beverages = 30.8% Clothing and footwear = 2.46% Housing, water, electricity, gas and other fuels = 16% Furnishing, housing equipment and routine maintenance of the house = 13.5%	Brizga et al., 2017

(continued on next page)

Table 1 (*continued*)

Country and tracking year	Household parameters	CO_2 tracking method	Emission estimate	Reference
	Transport Communications Recreation and culture Education Restaurants and hotels		Health = 1.2% Transport = 30.8% Communication = 0% Recreation and culture = 2.46% Education = 0% Restaurants and hotels = 1.23% Miscellaneous goods and services = 1.23%	
Korea (2013)	Monthly use of electricity, liquefied natural gas, oil, and liquefied petroleum gas, and transportation	Carbon intensities (tCO_2) = Consumption × Emission factor	Electricity (summer) = 79% Electricity (winter) = 59% Liquefied natural gas (summer) = 34% Liquefied natural gas (winter) = 15%	Kim & Kim, 2013

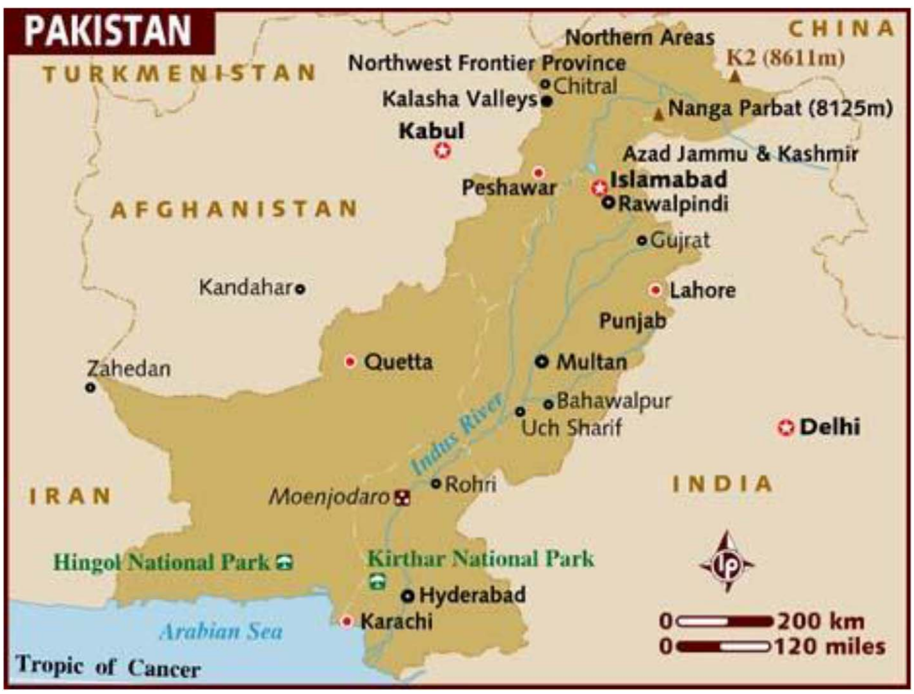

Fig. 2. Map of Pakistan showing research area.

and also consumption of petrol (L) and CNG (Kg) were asked in questionnaire. Data of natural gas (hm3) was collected through their monthly bills from each household. While the data of food and other secondary factors were also collected as the requirement of the questionnaire. Data were collected from households located in different areas of Rawalpindi city and the questionnaire comprised of parameters given in Table 2.

2.1. Carbon footprint calculations

Collected data was entered into the carbon footprint calculator to find out the carbon footprint (http://www.carbonfootprint.com/calculator.aspx). The total carbon footprint of household was measured as the product of household consumption such as spending on different sectors and the emissions per unit of consumption in activities include in parameters. The household carbon footprint (HCF) can be calculated by using the equation (Shirley et al., 2012).

$$\text{HCF } (tCO_2e) = \text{Average Annual Spending} \times \text{Emissions Factor}$$

An emission factor is the standard value of each parameter. An emissions factor of carbon footprint is the standard amount of CO_2 emits as per unit of consumption.

3. Statistical analysis

Data was processed for mean, standard deviation, linear regression and correlation in order to find the association among household parameters and CO_2 emissions. The statistical analysis was carried out in Microsoft Excel® 2003.

Table 2
Household parameters used in questionnaire for data collection.

House energy consumption	Economic and social variables	Secondary factors
Electricity (kWh per year)	Number of family members	Fashion
Natural gas (Btu per year)	Income (in Rs.) per month	Packaging
Transportation (km per year)		Furniture or electrical equipment
Food (preference type of food)		Recycling
		Recreation
		Finance and other services

Table 3
Statistical description of Bahria Town, Gulraiz Colony, Khayaban-e-Sirsyed and Kachi Abadi.

Variables	Bahria Town (n = 20)	Gulraiz Colony (n = 20)	Khayaban-e-Sirsyed (n = 20)	Kachi Abadi (n = 20)
Income of respondents				
< 20,000	0	0	13	14
20,000–40,000	0	5	7	6
40,000–60,000	0	8	0	0
> 60,000	20	7	0	0
Type of vehicle				
Car				
CNG	11	12	0	0
Diesel	0	0	0	0
Petrol	9	8	0	0
Model of car				
Large	8	4	0	0
Medium	12	16	0	0
Model of motorbike				
Large	0	0	0	0
Medium	1	3	1	2
Type of food preference				
Vegetables	1	2	17	18
Mainly fish	0	0	0	0
Mainly white meat	4	5	3	2
Mix of white and red meat	15	13	0	0
Use of certified organic food				
Most of times	10	8	0	0
Some times	10	9	4	11
Don't notice	0	3	16	9
Use of imported food and goods				
Buy locally	7	12	0	0
Most of times	4	1	0	0
Prefer goods closer to home	9	6	8	4
Don't notice	0	1	12	16
Fashion trend following				
Buy with latest fashion	13	9	0	0
Buy when need them	7	11	12	5
Buy second hand cloth	0	0	8	15
Use of pack items				
Only buy things that are nicely packed	8	8	0	0
Try buy things with little packaging	12	8	7	3
I ignore packaging	0	4	13	17
Furniture and electrical items				
Buy latest technology	5	4	0	0
Buy new items after 5 years	9	3	0	0
Buy essential until it wear out	6	13	3	0
Buy used items	0	0	17	20
Waste recycling				
Most of waste is recycled	0	0	0	0
Some of waste is recycled	20	0	0	0
My home waste is not recycled	0	20	20	20
Carbon neutral habits				
Only do zero carbon activity	0	2	20	20
Occasionally go out to places like restaurants	8	9	0	0
Mostly ignore C impact	12	9	0	0
Enjoy carbon intensive activity	0	0	0	0
Don't have bank account	4	7	20	20
Use of standard range of financial services	16	13	0	0

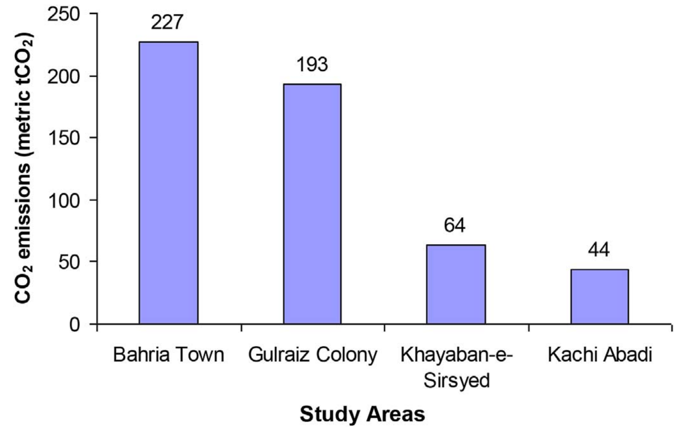

Fig. 3. Distribution of carbon footprint among selected areas of Rawalpindi.

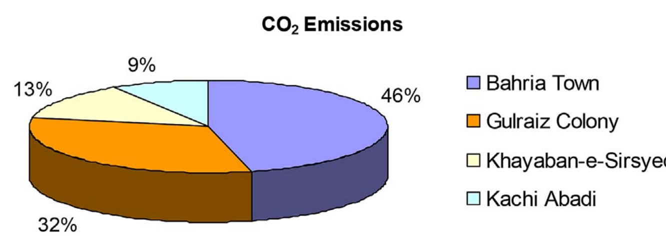

Fig. 4. Percentage wise distribution of CO_2 emission in selected areas of Rawalpindi.

4. Results and discussion

Rawalpindi is a standout amongst the most urbanized urban communities of Pakistan having population of 4.5 million. Household characteristics used in the analysis of household emissions and data collected from selected population are presented in Table 3. Information about household size, annual household income, number of vehicles owned and other demographic variables including food, fuel, transport, waste management are presented here. The outcomes clearly showed that Bahria Town have higher carbon footprint when contrasted with other territories (Fig. 3). Carbon footprint contribution of each area in percentage is shown in Fig. 4 which demonstrates that Bahria Town has highest contribution in carbon footprint percentage (46%) while Gulraiz Colony was found to be the second highest (32%) in carbon footprint. Khayaban-e-Sirsyed has carbon footprint of 13% while Kachi Abadi has the lowest value regarding carbon footprint i.e.9%. The main reason for highest contribution of Bahria Town in carbon footprint is their luxurious life style and high energy consumption practices. As the income increases, the households tend to achieve high carbon categories which were not affordable for them in past (Weber & Matthews, 2008). Carbon emissions increase specifically due to higher transportation and electricity and indirectly because of other secondary factors such as recycling, recreation, food, fashion and clothing (Tukker & Jansen, 2006). Because of intensive transportation and power utilization, individuals of Bahria Town and Gulraiz Colony has higher carbon footprint. These results are consistent with the study of Druckman and Jackson (2008) which reported that in UK high

Table 4
Correlation matrix of household size, income and per household carbon footprint of slum and non-slum areas of Rawalpindi.

	1	2	3	4	5	6
Non-slum areas						
1. Household members of Bahria	1					
2. Monthly income of Bahria (Rs)	**875000** (r = 0.59) (p = .006)	1				
3. Per household CFP of Bahria	**11.3** (r = 0.91) (p = .00)	(r = 0.49) (p = .027)	1			
4. Household members of Gulraiz	**4.8** (r = 0.13) (p = .59)	(r = −0.05) (p = .84)	(r = 0.14) (p = .55)	1		
5. Monthly income of Gulraiz (Rs)	**69000** (r = −0.15) (p = .52)	(r = −0.41) (p = .07)	(r = 0.05) (p = .84)	(r = 0.29) (p = .22)	1	
6. Per household CFP of Gulraiz	**9.6** (r = 0.09) (p = .71)	(r = −0.12) (p = .60)	(r = 0.22) (p = .36)	(r = 0.06) (p = .79)	(r = 0.79) (p = .00)	1
Slum areas						
1. Household members of KA	1					
2. Monthly income of KA (Rs)	**1100** (r = 0.42) (p = .06)	1				
3. Per household CFP of KA	**2.2** (r = 0.01) (p = .96)	(r = 0.76) (p = .00)	1			
4. Household members of KSS	**6.5** (r = −0.09) (p = .69)	(r = 0.28) (p = .23)	(r = 0.25) (p = .29)	1		
5. Monthly income of KSS (Rs)	**14350** (r = −0.17) (p = .47)	(r = 0.18) (p = .43)	(r = 0.40) (p = .08)	(r = 0.47) (p = .03)	1	
6. Per household CFP of KSS	**3.2** (r = −0.32) (p = .16)	(r = 0.25) (p = .28)	(r = 0.60) (p = .05)	(r = 0.40) (p = .07)	(r = 0.84) (p = .0)	1

Bold values = Mean, CFP = Carbon footprint, KA= Kachi Abadi, KSS = Khayaban Sirsyed.

proportion of CO_2 emissions in households is due to direct energy consumption. Considering the fact that low carbon housing seems imperative to achieve urban sustainability (Ho, Matsuoka, Simson, & Gomi, 2013) preference to energy efficient housing and transport systems needs to be emphasized in new urban areas to facilitate low carbon emissions (Li, Quan, & Yang, 2016).

Correlation matrix of household size, monthly income and per household carbon footprint of slum and non-slum areas of Rawalpindi represented by their mean values, correlation values and their level of significance (Table 4). Bahria Town shows highly significant increment in per household carbon footprint with their increasing monthly income ($r = 0.49$ $p = .02$). Although the family members of non-slum areas are limited than slum areas but they all have larger contribution in earning which results in higher carbon footprint. While 91% variability in per household carbon footprint of Bahria Town has significant positive correlation with average household members ($r = 0.91$; $p < .01$). Indiscriminate use of carbon intensive products by all the members of non-slum areas might have contributed in high carbon footprint. On the other hand 79% variability in per household carbon footprint of Gulraiz Colony is correlated with their monthly income ($p < .01$) (Table 4). A highly significant correlation of monthly income with per household carbon footprint of Kachi Abadi and Khayaban-e-Sirsyed in slum areas ($r = 0.76$; $p < .01$) ($r = 0.84$; $p < .01$) respectively shows that the income of the household members is the major factor in increasing carbon footprint although the inhabitants of slum areas have lower income value than non-slum areas so their carbon footprint are much lower than non-slum areas because they are not able to avail more facilities and tend to spend life without any luxuries which is a major cause of their reduced carbon footprint compared to non-slum areas. Residents having increasing household income spent more money on enhancing their life quality by buying energy intensive items including private vehicles and home vitality apparatuses and they also have facilities to getting a charge out of high carbon way of life by taking abroad travel (Hubacek, Guan, Barrett, & Wiedmann, 2009; Tian, Chang, Lin, & Tanikawa, 2014). Carbon footprint values for per capita and per household of non-slum areas were higher than the slum areas (Fig. 5). Bahria Town per capita average CO_2 emission was 3.1(tonnes) while the average value of CO_2 emission for Gulraiz Colony is estimated to be 2 metric tCO_2 per capita. Khayaban-e-Sirsyed and Kachi Abadi are estimated to be 0.4 metric tCo_2 and 0.1 metric tCO_2 per capita average CO_2 emissions respectively (Fig. 5). Per capita and per household energy consumption highly depends not only on the geographic and climatic conditions but also on energy supply infrastructure (Sanches-Pereira, Tudeschini, & Coelho, 2016). As urban areas are generally economically well off, so their per capita consumption is expected to be

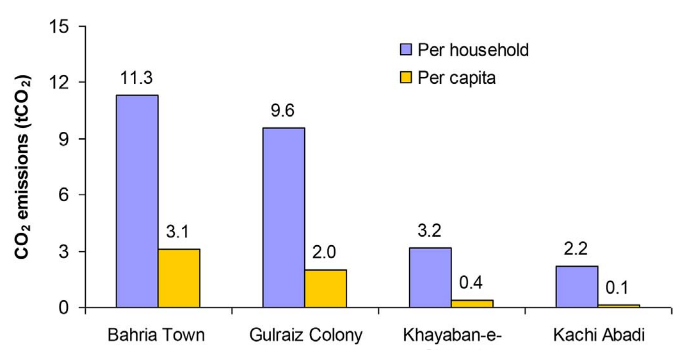

Fig. 5. Per household and per capita carbon footprints for the Bahria Town, Gulraiz Colony, Khayaban-e-Sirsyed and Kachi Abadi.

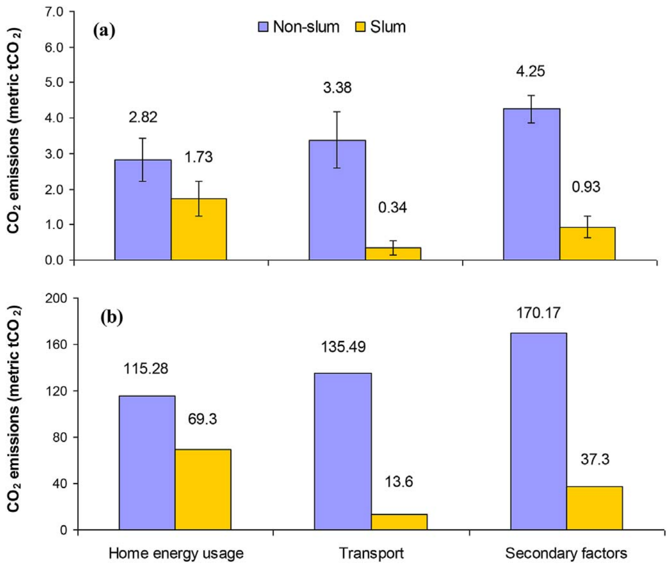

Fig. 6. Sector wise comparison of CO_2 emissions between slum and non-slum areas of Rawalpindi. (a) mean values, (b) total emissions.

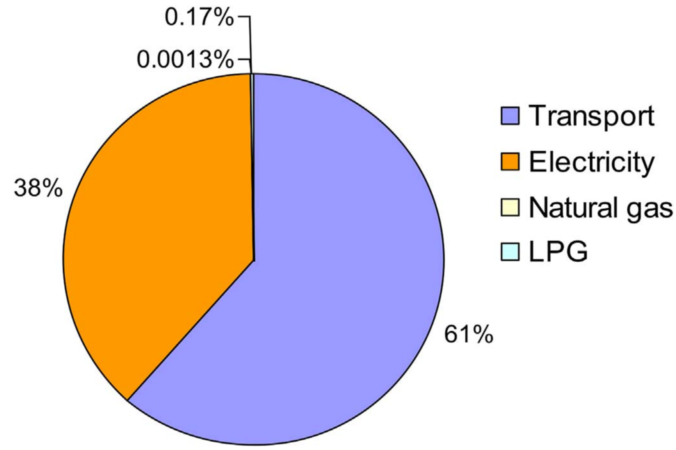

Fig. 7. Percentage wise distribution of carbon footprint in different sectors from Non-slum areas of Rawalpindi.

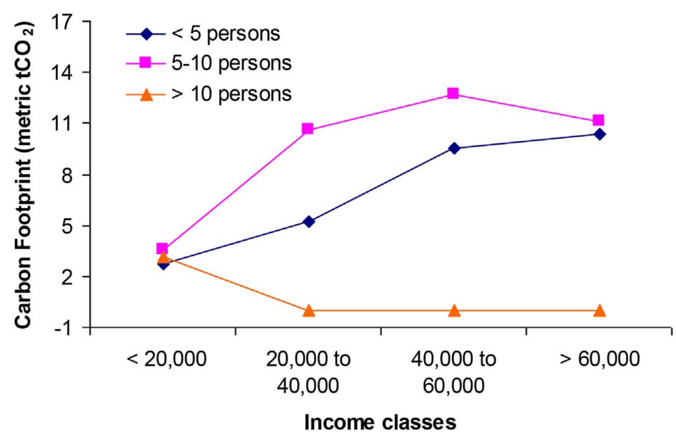

Fig. 8. Relationship between monthly income (Rupees) and carbon footprint categorized on household size.

higher, while from household size and monthly income perspective, slum areas have generally larger household size than non-slum areas which is due to the number of children in each household of slum areas are generally higher than the non-slum that is probably the reason behind the higher carbon footprint of non-slum areas, as reported in Gough, Abdallah, Johnson, Ryan-Collins, and Smith (2011) children probably consume less than adults that's why their per capita emissions are lower in slum households.

Bahria Town and Gulraiz Colony are financially well off areas when contrasted with Khayaban-e-Sirsyed and Kachi Abadi, so it makes an fascinating comparison in household utilization and carbon footprint. Non-slum areas show highest mean and total CO_2 emissions in energy usage, transport sectors and in secondary footprint (Fig. 6a and b). High carbon footprint might be due to large number of electric appliances used in non-slum areas such as A.C, television, mobile phones and internet consume high energy. Major reason behind higher CO_2 emissions in non-slum areas is the utilization of individual transport rather than public transport while in slum areas individuals scarcely utilize individual transport. Increment in gaseous emissions as lead and other toxic substances from transport sector contribute in higher carbon footprint as Padgett et al. (2008) exhibits a correlation over various well known US household carbon calculators which shows that the most prevailing contributor in total carbon footprint is the fuel used for private transportation. People like to buy more vehicles and choose significantly bigger apartments to live in or even independent houses with more home appliances due to their increasing income, bringing about more energy consumption (Tian, Geng Dai et al., 2016; Tian, Geng, Dong et al., 2016).

Transportation has highest percentage of CO_2 emissions in comparison to all household components of non-slum areas (Fig. 7). The higher transport emissions probably due to that there is no any public transport in Bahria Town so most of people use personal transport which increase CO_2 emissions. Electricity consumption and intensive transportation results in increase in carbon footprint in non-slum areas and similar results were shown in Kerkhof et al. (2009) which reported that CO_2 emissions intensity of transport is high in Norway, Sweden, Netherlands and UK, which is mainly the result of high emissions intensity of gasoline. The contribution of LPG and natural gas consumption in our results were very low as compared to transportation and electricity because these household have more expenses on personal vehicles and communications for example internet and cell phones. Our results are also consistent with other studies, which demonstrate that in higher income areas, transportation and manufactured goods are usually a larger share of household footprint, whereas in developing areas food and utility services are more vital (Bin & Dowlatabadi, 2005).

Less than 5 person household size and highest income shows significant dependence on increasing carbon footprint (p-value = .02) (Fig. 8). Regression coefficient also represent high association between the household size for < 5 persons and carbon footprint i.e. 94%. For other two household sizes (5–10 person and > 10 person) the association though is non-significant but the regression coefficient is 0.6. The significant association of carbon footprint with < 5 persons represent that these are mostly non slum households with high income and these have great potential to increasing footprint value because they need more services and goods to meet their demands of luxurious life style with the increasing urbanization. Since individuals with high salary utilize a bigger number of assets than individuals of lower pay. From Chinese household constant increment of indirect CO_2 emissions was observed with the increasing income and increasing urbanization in both urban and rural households (Liu, Wu, Wang, & Wei, 2011). Individuals with high income value utilize great number of resources than the general population of low pay premise, so as compared to low income acquiring individuals, high income earning people have more carbon footprints (Galli et al., 2012).

Increasing carbon footprint in non-slum areas shows significant relation with annual distance traveled by personal vehicles (R^2 value 0.613) (Fig. 9). As carbon footprint relies upon distance traveled by personal vehicle so regression analysis shows that the carbon footprint value also increases by expanding traveled distance. This increment might be due to that if each person uses its own car than the rate of CO_2

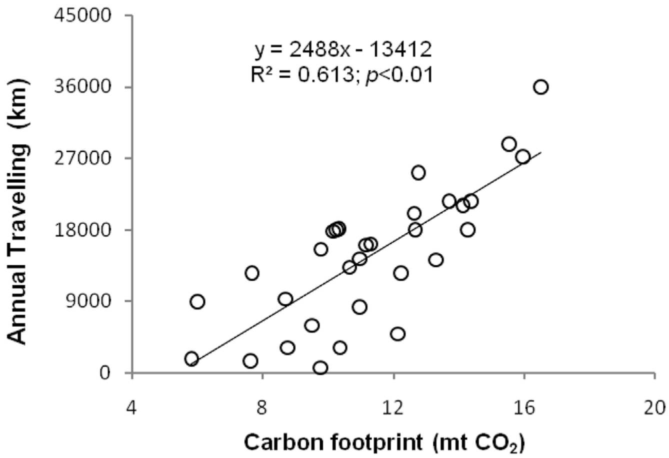

Fig. 9. Regression between Carbon footprint and annual distance traveled on personal vehicles by residents from Bahria Town and Gulraiz Colony.

emissions are higher as compared to large number of people use one public transport. CO_2 emissions due to personal transport from the urbanized areas are also increased due to increased number of population migrating toward urbanized areas. Jones and Kammen (2011) found that in US household, distance traveled through direct engine fuel is the biggest contributor in total carbon footprint instead of other parameters such as natural gas, food, medicinal services and power. High quantities of fuel used in personal vehicles are responsible for increasing carbon footprint. Many citizens of urbanized areas daily need to cover long distances for their work in big cities which results in increase in carbon footprint (Tian, Geng Dai et al., 2016; Tian, Geng, Dong et al., 2016).

In the backdrop of rapid urbanization as noticed in this study, our results highlight the need of urgent intervention strategies to reduce the size of carbon footprint at household level. In particular, non-slum areas may transform consumption patterns by adopting less energy intensive steps such utilizing public transport, insulating homes and use of energy efficient appliances. Introducing solar panels at homes could shift dependence from non renewable resource utilization in non-slum areas followed by green electricity consumption that can significantly reduce the carbon footprint. At personal level, adopting carbon friendly habits that lead to low energy demand in household can minimize CO_2 emissions (Fan, Guo, Marinova, Wu, & Zhao, 2012). One of the limitations of this study is small sample size however, this appears to be the first investigation of focusing household carbon footprint analysis, further work involving extensive survey would now be possible using the methodological framework mentioned here.

5. Conclusions

Urgent attention is needed in Pakistan to transform rapidly growing urbanized regions into a low carbon society. Currently, more than 30 million metric tons of annual carbon emission is recorded, which in global emission accounts only 0.4%. Despite of its small global share, the national values clinched almost four times since 1980 when it was only 9 million metric tons. Carbon footprint of any region profoundly rely on housing and hence rational approaches are needed to curtail carbon emission in cities such as low carbon Hong Kong is dreamed by Choy, Ho, and Mak (2013) who proposed an incentive based carbon reducing approach for electricity users to minimize housing carbon footprint. Our study has clearly indicated that housing and lifestyle in non-slum areas are lavish with high carbon footprint. It is recommended that advancement of green transportation, less fuel use, and integration of planning, construction engineering and urban design will eventually develop efficiency in energy performance that will led to create low carbon urbanized regions.

Acknowledgements

Authors are grateful to all respondents who participated in the study. Without their cooperation, this study would have not been possible.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.habitatint.2017.12.012.

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